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ABSTRACT

Background: Investigators have examined whether heat mortality risk is increased in neighbourhoods subject to the urban heat island (UHI) effect, but not identified degree of difference in susceptibility to heat and cold between cooler and hotter area, which we call as acclimatization to the UHI.

Objectives: To develop methods to examine and quantify the degree of acclimatization to heat- and cold-related mortality in relation to UHI anomaly, then apply to London, UK.

Methods: Case-crossover analyses were undertaken on 1993-2006 mortality data from London UHI decile groups defined by anomalies from the London average of modelled air temperature at 1km grid resolution. We estimated how (i) UHI anomalies modified excess mortality on days cold and hot for London overall and (ii) displaced a fixed shape temperature-mortality function (‘shifted spline’ model). For each we also compared observed associations with those expected under *no* or *full* acclimatization to the UHI.

Results: The relative risk of death on hot compared to normal days differed very little across UHI decile groups. A 1°C UHI anomaly multiplied the risk of heat death by 1.004 (95% CI 0.950, 1.061) (interaction rate ratio) compared with 1.070 (1.057, 1.082) expected if there were *no* acclimatization. The corresponding UHI interaction for cold was 1.020 (0.979, 1.063) against 1.030 (1.026, 1.034) expected. Fitted splines for heat shifted little across UHI decile groups, again suggesting acclimatization. For cold, they shifted somewhat in the direction of *no* acclimatization, but not excluding acclimatization.

Conclusions: We have proposed two analytical methods for estimating the degree of acclimatization to the heat- and cold-related mortality burdens associated with UHI. The results for London suggest relatively complete acclimatization to the UHI effect on summer heat-related mortality, but less clear evidence for cold.

INTRODUCTION

It is well recognised that urban areas can experience ambient temperatures appreciably warmer than surrounding rural areas – a phenomenon known as the urban heat island (UHI) effect (Oke 1982). The primary cause is the built environment which absorbs and stores heat more than natural landscapes, while waste heat generated by energy processes in buildings, transport systems and industry is a second, usually less important, factor in the UK (Bohnenstengel et al. 2011; Bohnenstengel et al. 2014). This might be different in south-east Asian or the US cities. Such variation of ambient temperature can also be observed within a city (warmer inner city and cooler outer city). The UHI effect is typically larger at night than during the day (Bohnenstengel et al. 2011; Wilby et al. 2011). From a health perspective, the additional summer heat of the UHI is of concern because of its potential exacerbation of heat-related health risks, which, in many settings, are projected to worsen as a consequence of climate change (Hajat et al. 2014; Vardoulakis et al. 2014). Many city authorities are actively considering how the UHI effect may be minimized by improved land-use planning, additional tree planting and other interventions. However, there is only limited direct empirical evidence on the magnitude of the UHI risks to health.

In this methodological research, our primary focus is the UHI effects operating within a city. Relatively few studies have explored *intra-city* variation in heat-related mortality (Gabriel and Endlicher 2011; Goggins et al. 2013; Harlan et al. 2013; Reid et al. 2009; Smargiassi et al. 2009; Vandentorren et al. 2006; Xu et al. 2013), which may arise not only because of the UHI effect (Harlan et al. 2013), but also because of variations in vulnerability of the population from such factors as population age or socio-economic deprivation (Reid et al. 2009; Xu et al. 2013). A study in Montreal (Smargiassi et al. 2009) found greater risk of death on hot summer days in areas with higher surface temperatures defined by satellite images, and a German study (Gabriel and Endlicher 2011) found a positive correlation between the excess mortality during periods of high heat stress and the proportion of land area covered by sealed surfaces in district. A case-control study of elderly deaths during the 2003 heat wave in France (Vandentorren et al. 2006) reported an increased risk of all-cause death in areas with a 1 ˚C higher surface temperature index which is generated from satellite thermal infrared images (adjusted odds ratio of 1.82; 95%CI 1.27, 2.60).

Where UHI effects have been studied, they have mainly been limited to analysis of heat effects, with very little focus on possible attenuation of cold effects: for instance, inner city areas may experience less cold-related deaths than outer city areas because of the UHI. Few studies have attempted to separate UHI influences from other sources of variation in population vulnerability such as socio-economic deprivation (Goggins et al. 2012) or population age. Moreover, to our knowledge, no studies have clarified if the size of the UHI-related excess of heat mortality is commensurate with how much hotter those areas were. Although multi-cities studies showed some evidence of possible adaptation or acclimatization to their local climate - hotter cities often do not experience as much increase in heat-related mortality over cooler cities as one would expect from how much hotter they are (Curriero et al. 2002) - it is not known if parts of cities experiencing more heat due to the UHI show any such decreased susceptibility.

In this study we present methods to determine whether hotter neighbourhoods (those affected by a UHI) have higher excess mortality on hot days (or lower mortality on cold days) allowing for adjustment of other factors, and to estimate the extent to which such differences are consistent with expectations given how much hotter or colder those areas are compared with London overall. For brevity, we refer to apparent differences in susceptibility to the effects of heat or cold among UHI anomaly decile groups as evidence for or against local acclimatization to the UHI. Here, we refer to a difference in susceptibility among neighbourhoods rather than a change in susceptibility over time within a single population. Underlying cause is unknown and may include physical component such as built environment and physiological mechanisms, whether such changes are consciously made to adapt or not (more restrictive uses in Gosling et al. (2014) and IPCC (2014)). This paper illustrates the methods and applies them to data from London 1993-2006, and considers modification of cold as well as heat effects by the UHI.

METHODS

Data

The study was based on an analysis of daily mortality for all-caused deaths in London, 1993-2006, with individual mortality records linked to the area of residence through the address postcode (on average 18 households or 43 residents per a residential postcode in England, data from the Office for National Statistics). A single London series of temperature for the same period was constructed as the population-weighted average of the daily mean temperatures at seven available monitoring sites, imputing missing values by the method of the AIRGENE study (Ruckerl et al. 2007). Details are in Armstrong et al. (2011).

In this study, UHI was considered as a primary modifier of main temperature effect on mortality. Socio-economic deprivation could also be a possible effect modifier of the temperature-mortality relationship, which might confound UHI effects (as an effect modifier) on temperature-mortality relationship (details below). As such, we assembled data on the English Index of Multiple Deprivation (EIMD) 2004 for the Lower layer Super Output Area (LSOA) of residence (Office of the Deputy Prime Minister 2004). LSOA is a unit of small area designed to be homogeneous in neighbourhood characteristics with relatively even population size of 1,500 residents on average. EIMD 2004 was modified by excluding two domains (the health and disability domains; and the living environment domain) that partially include variables to be incorporated in the main analytical model (small-areal statistics of mortality; and ambient concentration of particulate matter and other air pollutants respectively) , keeping the overall weights of six remaining domains (income; employment; education, skills and training; barriers to housing and services; crime) proportional to those in the original index, following to the approaches conducted by previous studies (Adams and White 2006; Goodman et al. 2011).

Single London series of air pollution levels for daily mean of PM_{10} (particulate matter having aerodynamic diameter less than 10 µm) and daily maximum of 8 hourly running mean of ozone (O_3) in 1993-2006 were also constructed from urban background and suburban monitoring sites located in Greater London (35 sites, 18 non-missing measures on average per day for PM_{10} and 29 sites, 15 non-missing measures for O_3). Pollution measurements were obtained from London Air Quality Network managed by King's College London (www.londonair.org.uk). Geographical data linkages were conducted in ArcGIS v10.0.

Modelling the UHI

In order to quantify the UHI, modelled ambient temperatures (°C) at 1.5m height were derived at 1km grid resolution in London from numerical simulations with the Met Office weather forecast model (Unified Model). Within the Unified Model a parameterization for urban land-use was used to calculate the exchange of heat, momentum and moisture between the urban land surface i.e. street canyons and the atmosphere. The Met Office Reading Surface Exchange Scheme (MORUSES) calculate the surface energy balance i.e. the sensible heat flux, storage of heat into the buildings and ground, long wave radiation and short wave radiation based on the geometry of street canyons. Details about the MORUSS parameterization are described elsewhere

(Bohnenstengel et al. 2011). For each day and each grid square, the excess temperature relative to the London mean for that day was calculated, and the daily excesses were averaged over all days in the available model data (May to August and December 2006). This is called the annual urban heat island anomaly (UHIa) and that at grid square *g* is expressed as:

$$UHIa_g = 1/n \sum_{j=1}^{n} \left(T_{gj} - \overline{T_j} \right)$$

where T_{gj} is the maximum temperature at grid *g* on day *j*, T_j the averaged daily mean temperature across all grids in London on day *j*, and *n* the number of days (n=154). All 1km grids (1,587 grids in London) were classified into decile groups based on the decile of distribution of grid UHI anomalies (UHIa) in London. Figure 1 presented spatial distribution of these UHI anomaly decile groups. Table 1 summarised averaged UHIa for each UHI decile and corresponding statistics.

Statistical methods

Analysis of the relationship between mortality risk and daily mean temperature was based on a case crossover analysis stratified by year, month and UHIa decile groups, using a conditional Poisson model (Armstrong et al. 2014). This can be equivalently thought of in case-control study terms as case-control sets, each comprising explanatory variable values for one case day (if there was a death that day) and 27-30 control days (same calendar year, month and UHI decile groups). All analyses controlled for day-of-week and count of circulating influenza (from the Communicable Diseases Surveillance Centre) by including these as explanatory variables.

Algebraically:

$Y_{ij} \sim Poisson\ (\mu_{ij}\ |\ deaths\ in\ UHI\ group\ i,\ year,\ month\ and\ day\ of\ week)$

$with \quad \mu_{ij} = exp\{(covariates) + (terms\ involving\ temperature\ t_j\ and\ UHIa_i\}$ [1]

Where:

Y_{ij} : death count on day j and UHI anomaly decile groups i

Covariates: linear sum of regression terms (coefficient * variable), $\sum \beta_i z_{i,t}$ for:

- deaths from influenza in England and Wales on day j
- indicator terms for days of the week

t_j : mean ambient temperature on average over all London on day j

$UHIa_i$: mean UHI anomaly (in degrees difference to London mean) in UHIa group i

The main effect of temperature on mortality was modelled separately for summer (June-August) and winter (September-May) with distributed lag non-linear models using the dlnm R package (Gasparrini 2011) with unconstrained lags 0-1 (same day and day before) for summer and a natural cubic spline lag structure with two knots (package default placement) over lags 0-13 for winter. The lag intervals were chosen based on previous work (Hajat et al. 2007). We modelled the impact of UHI on temperature effects using two approaches: a crude one, similar to methods used previously (Goggins et al. 2013; Smargiassi et al. 2009; Vandentorren et al. 2006) and a more sophisticated but possibly less transparent one.

(i) Comparison of the risk for deaths on hot and cold days (relative to that on days with moderate temperatures) at UHIa of +0.5 and -0.5 °C

For this analysis, the heat and cold risks were modelled (separately for each season) as simple dichotomies: indicators for "hot" and "cold" days:

$$\mu_{ij} = exp\{(covariates)+dlnmA(t_j)\} \qquad [2]$$

where dlnmA is a dlnm with temperature dichotomy (hot or cold day) and lag structure as described for model [1].

Cut-points used to define hot and cold day indicators were 22.3 and 6.4 °C, chosen as those which gave most significant risk excesses, measured by the Wald z = log(RR)/SE(log(RR), over a range of trial values (Figure S1).

We modelled the UHIa modification of these hot and cold-related mortality risks as interaction (product) terms for each dlnm sub-term:

$$\mu_{ij} = exp\{(covariates)+dlnmA(t_j)+ \theta.UHIa_i.\ dlnmA(t_j)\} \quad [3]$$

We present the results from the fitted models as the relative change in these predicted heat (cold) mortality ratios for an UHIa of +0.5 °C compared with that at an UHIa of -0.5 °C (one degree difference). We call this relative change associated with one degree UHIa the interaction rate ratio (IRR). One degree of UHI anomaly is slightly less than the difference in mean anomaly between the lowest and the highest UHIa decile group (-0.93 and 0.63 °C, respectively, range 1.56).

These IRRs estimate the increased risk on hot days found in areas of London subject to the UHI compared to areas typically one degree cooler UHIa (and analogously for cold). We sought to compare these with what would be expected from how much risk increases in London overall when days get one degree hotter (colder). To do this we estimate the heat (cold) slope of mortality increment in association with London-wide daily mean temperature ignoring the modification by UHI of temperature-mortality relationship. This model was the same as model [2] above but fitting the temperature effect as a linear spline (segmented linear model) with knots at 18.6 (the minimum mortality temperature, MMT, in a natural cubic spline all-year model) and 22.3°C for heat (Figure S2), and 6.4 and 18.6°C for cold. The expected IRR for heat was estimated as the slope in the spline above the highest knot (below the lowest for cold). IRRs for heat at the expected value indicates no acclimatization to heat in an UHI and IRRs below that value indicates a degree of such acclimatization (reduced vulnerability).

(ii) Comparison of the displacement, parallel to the temperature axis, of a fixed-shape temperature-mortality function at UHIa of +0.5 and -0.5 °C

The second method entailed fitting a temperature-mortality curve for each season (natural cubic splines) and quantifying the displacement of this function parallel to the temperature axis at different UHIas under the constraint that the function has identical shape at all UHIas and that is displaced linearly with the UHIa. Algebraically:

$$\mu_{ij} = exp\{(covariates)+dlnmB(t_j + \gamma UHIa_i)\} \qquad [4]$$

With dlnmB(t) having a natural cubic spline temperature function ncs with 4df (chosen a priori by experience).

The extent to which the curve was displaced by the UHIa (γ) was estimated by calculating likelihoods (deviances) over a grid of candidate values and thereby obtaining the maximum likelihood estimate. We refer to this as the 'shifted spline' method. As with method (i), though UHIa was again fitted as a continuous variable we report the extent that the splines were shifted from an UHIa of +0.5 °C to an UHIa of -0.5 °C.

The results of the 'shifted splines' analysis are shown in terms of the displacement parameter, γ, which, for heat, represents the displacement of the temperature-mortality function for one degree UHIa, for example at UHIa of +0.5 °C compared with that at UHIa of -0.5 °C. If there is *no* acclimatization, γ takes the value 1, indicating that the observed curves (at UHIa +0.5 and -0.5 °C) are separated by the actual temperature differences between those areas – namely, 1 °C in this instance (Figure S3[A]). Under *full* acclimatization, γ takes the value 0 and the curves at UHIas of +0.5 and -0.5 °C will be superimposed as the population exhibits the same temperature-mortality function (shape and location with respect to the single temperature series) in all areas (Figure S3[B]). The same interpretation applies for cold-related mortality, but with comparison of the curves at UHIa reversed: -0.5 vs +0.5 °C.

Differences between deviances at the fitted value for $\gamma=0$ and $\gamma=1$ provide likelihood ratio tests against null hypotheses of full and no acclimatization respectively.

Key to the interpretation of both measures of effect modification by the UHIa is that, in our analyses, the temperature-mortality relationship was based on a single London 'average' temperature series. This means that the actual temperature experienced by the population at grid locations with positive UHIa is underestimated by the single series, while those with negative UHIa is overestimated. Thus, if the true temperature-mortality relationship is identical in all locations of London, regardless of the UHIa (we call this *full* acclimatization), then we would expect higher relative risks for heat in areas with a positive UHIa because actual temperatures are higher than indicated by the single temperature. Similarly there would be lower relative risks for heat in areas with a negative UHIa because actual temperatures would be lower than indicated by the single series.

Control for other possible biases of the UHI effect

Although age and socio-economic deprivation are time invariant in the context of this analysis, so not potential confounders in the usual sense, they both could confound the estimated modification of heat (cold) - mortality associations (IRR) by UHI if they also modified those associations. We controlled for this in additional analyses. For socio-economic deprivation we entered an average of reconstructed EIMD scores by UHI decile groups into the simpler model (method (i)) as a second modifier of heat and cold (i.e. further interaction terms in model [3]).

Also we checked whether socio-economic deprivation actually modifies the heat- and cold-related mortality associations as the first modifier. For age, because of its stronger expected modification of heat and cold risks, we instead stratified our main analyses by age groups (aged 0-64, 65-74, over 75 years) especially focusing on the elderly people who are known to be more vulnerable to heat and cold effects. Ambient pollution (O_3 and PM_{10}) are time varying risk factors, so we adjust for their effects by directly including them in the model as linear terms, though we note that this might be better considered as controlling for indirect temperature effects mediated through O_3 and PM_{10} than simply controlling confounding (Buckley et al. 2014).

As a sensitivity analysis, we repeated main analyses with shortened non-summer months (October – April) to reduce possible confounding by heat in September and May. All confidence intervals (CIs) shown in results represent 95%CIs. Statistical analyses were conducted in R v3.0.2 and R code is available for individual request to authors.

RESULTS

Hot and cold vs moderate temperature periods

Results of the comparison of the mortality risks in the hot and cold temperature range relative to that in the moderate temperature range are shown in Table 2. In the unadjusted analysis, the point estimate of the heat-related mortality risk at the UHIa of +0.5 °C was 1.208 (CI: 1.176, 1.241), slightly higher than the 1.203 (1.154, 1.255) at the UHIa of -0.5 °C. The confidence interval for the ratio (IRR) was compatible with no difference (1.004, CI: 0.950, 1.061). This IRR compares with an expected ratio of 1.070 (CI: 1.057, 1.082) if no acclimatization is assumed – i.e. if areas at different UHIas have the same level of risk in relation to the *actual* temperatures experienced in those areas. Thus, the observed results suggest only small differences in heat risk between areas with anomalies at +0.5 °C and -0.5 °C compared to expected IRR assuming *no* acclimatization, a finding most compatible with a fairly high degree of acclimatization to heat. This is the situation in which the heat-related relative risks in relation to the single temperature series are similar in all areas irrespective of the UHIa.

The point estimate results for cold-related mortality suggest a larger relative difference between areas with the UHIa of -0.5 °C compared with those with the UHIa of +0.5 °C in the unadjusted analyses (IRR=1.020, CI: 0.979,1.063), but the confidence interval was compatible with no difference. This figure compares with an expected IRR for cold mortality (if *no* acclimatization is assumed) in UHIa -0.5 *vs* +0.5 °C of 1.030 (CI: 1.026, 1.034). Although the point estimate of observed IRR (1.02) suggests weak evidence against acclimatization to UHI cold, its wider confidence interval and the relatively small expected IRR (1.030 for cold, compared to 1.070 for heat) means the result is compatible with both *no* and *full* acclimatization.

'Shifted splines' analysis

The point estimate of γ for the actual displacement we observed for the high temperature-mortality function in summer was 0 (Figure 2[A]). Comparison of deviances indicated that the results were compatible with *full* acclimatization to heat but not compatible with *no* acclimatization (p=0.02 by likelihood ratio test). For the low temperature-mortality relationship, the point estimate of γ was 0.8, thus close to that expected with *no* acclimatization (Figure 2[B]). However, deviances (i.e. likelihoods) varied little across the range between *full* and *no* acclimatization (γ=0 to 1) indicating that the data were compatible with both hypotheses - neither hypothesis of *full* nor *no* acclimatization to UHI cold would be rejected in a likelihood ratio test.

Control for other possible biases of the UHI effect

Little change was observed in heat- or cold-related mortality risk and IRR at different UHIas (the first effect modifier of temperature-mortality relationship) after adjusting for socio-economic deprivation (an additional potential modifier of temperature effects), although the point estimates for both became marginally less than 1 with wider confidence intervals (see Table S1). When we looked at socio-economic deprivation as a modifier of interest socio-economic deprivation itself did not show statistically significant modification of heat or cold effect on mortality (unadjusted IRR 1.010, CI 0.949 and 1.074 for heat; and IRR 1.02, CI 0.980 and 1.076 for cold), though wide confidence intervals did not rule out the possibility of modification (Table S2). Stratification by age-groups did not show much difference in IRR from those overall, although heat- and cold-related relative risks were highest in the age group over 75 years (Table S3; p value for Cochran's Q test of heterogeneity 0.996 for heat and 0.811 for cold). In the 'shifted splines' analyses of the mortality among the elderly only, the point estimate of γ was 0.3 for both low and high temperature-mortality relationship, which attenuated the evidence against *no* acclimatization to UHI heat (p=0.16 vs 0.02 for all ages, see Figure S4).

After adjusting for O_3 and PM_{10}, relative risks for heat got slightly lower in both hotter and cooler areas, thus little change in ratio, IRR itself (1.004, 95%CI 0.950, 1.061), which still remained in conflict with a slightly diminished expected one under the *no* acclimatization assumption (1.059, 95%CI 1.046, 1.073) (Table S4). In the 'shifted splines' analyses with adjustment of O_3 and PM_{10}, the point estimate of γ for the high temperature-mortality relationship remained close to *full* acclimatization (γ =0) and comparison of deviances showed robust evidence against *no* acclimatization (p=0.03 by likelihood ratio test) (Figure S5). The estimate of the acclimatization parameter, γ for the low temperature-mortality relationship diminished after adjusting for O_3 and PM_{10}.

Finally, a sensitivity analysis with shortened non-summer months (October – April) showed little difference in the results (Table S5). Accordingly, the overall findings remain indicative of acclimatization to UHI heat and compatible with both *no* and *full* acclimatization to UHI cold.

DISCUSSION

Summary of findings

This paper describes a formal approach for quantifying the degree to which populations within the same city are acclimatized to exposure to the higher outdoor temperatures arising from the UHI effect. We presented two methods: one based on simple comparison of the heat- (cold-) related relative risk at different UHIas, and another based on assessment of the degree of lateral displacement (parallel to the temperature axis) at different UHIas of a temperature-mortality relationship constrained to be fixed in shape. With the latter, in cases where there is *no* acclimatization, the estimated displacement should exactly match the UHIa. Where there is *full* acclimatization, the temperature-mortality relationships for all areas (based on an analysis which uses the same single 'city average' temperature series) should exactly coincide, such that the *actual* temperature-mortality functions have altered to such a degree that any day's mortality risk in the presence of the UHIa is the same as on the same day in areas with zero anomaly. The proposed methods compare heat- and cold-related mortality among areas with different UHI anomaly (specifically hotter and colder area) rather than over time, which we used as an indirect method to assess acclimatization to UHI. Application of these methods to London provides some evidence that areas of London subject to UHI-related higher temperatures in summer have largely acclimatized to them, as both the simpler and 'shifted splines' analyses suggest that heat risk depended on London-wide average temperatures and was not higher where actual local temperatures were higher. However, in relation to cold risk the evidence is somewhat mixed. Before adjustment for socio-economic deprivation results were closer to a situation in which cold risk was reduced where actual local temperatures were higher (i.e. little acclimatization), but not after adjustment. Whether adjusted or not results were compatible with *full* as well as *no* acclimatization.

If the lack of increased heat risk in localities with high UHIa indeed reflects acclimatization such as observed as `adaptation' in Petkova et al. (2014) over longer period, this has some relevance to future high temperature risks under climate change, but it is questionable whether populations would adapt as completely to the rapid and potentially more extreme temperature increments that may results from global warming.

Strengths and limitations

The analyses we present have a number of strengths and weaknesses. Among the strengths are the comparative richness of data, with fine geographical coding of death records, and detailed socio-economic and other data available at small area level, together with the size of the London population, which aids precision because of the comparatively high number of deaths per day. On the other hand, even though a sophisticated model was used for assessing temperature variations across London, the UHIa was based on analysis of a comparatively short time period (four summer months and one winter month in one specific year at the end of our 14 year mortality series) due to limited resource of this project. The use of the annual average UHIa as a marker of the UHI effect could also be debated. However, separate summer and winter UHIas were calculated for each grid in exploratory analyses (methods identical to those for all-year calculations) and found to be highly correlated with annual averaged UHIas in this study period.

This suggests that having UHIa estimates from a greater proportion of the study period in London would change results little.

In addition, we controlled only for limited potential biases of the UHI effect, namely, socio-economic deprivation, age structure of population, and selected air pollution levels. Our point estimate of UHI IRRs were robust to adjustment for socio-economic deprivation aside from reducing precision, but since deprivation has not been found to be related to heat mortality risk in London (Ishigami et al. 2008) or either heat or cold mortality risk in urban area in England and Wales (Hajat et al. 2007) such adjustment is arguably unnecessary. A possible reason for little association being observed in the UK between heat- and cold-related mortality and socio-economic deprivation could be generally low prevalence of air-conditioning usage and thus socio-economic disparities mediated through air-conditioning may not be apparent in the UK compared to the US cities (Madrigano et al. 2015). We did not attempt more detailed assessment of other variations in the population such as ethnicity (though somewhat related with socio-economic status) or infrastructure by UHI decile groups.

It is generally known that changes in daily ambient temperature influence local air pollution levels, such as ozone levels elevated by high temperature through effects on reaction kinetics (Reid et al. 2012) and chemical composition of particulate matter is possibly influenced by increased energy consumption (Anderson et al. 2012). Our main results reflected total effect of temperature on mortality without controlling for mediation through such air pollution levels. A sensitivity analysis, however, confirmed that the observed relations were robust to control for indirect mediated effects of temperature through O_3 and PM_{10}.

Another limitation was that the UHIas only reflect outdoor temperature differences at 1.5m above the land surface. This may be appreciably different from the actual temperature exposures experienced by people taking account of indoor exposures (Barnett 2015) which may be modified by building characteristics (Mavrogianni et al. 2012) and overshadowing by taller buildings in the city centre.

The analytical methods we proposed are the first, we believe, to quantify the extent to which modification of response to heat (or cold) in UHIa corresponds to that expected with *no* as well as *full* acclimatization. They can be interpreted as providing formal quantification of *the degree* of acclimatization to the UHIas. The first cost of doing this was complexity in interpretation, even for the simpler 'hot and cold periods' analysis. The second cost (limitation) was the need to choose from a wide variety of possible specific models. Our proposed markers of acclimatization are not the only possible measure of acclimatization, which could also be parameterized in terms of the threshold for the heat effect in a linear threshold model, or as a change in the slope of the exposure-response function, among other possibilities. For example, a several studies compared the MMT values across cities (Baccini et al. 2008; Baccini et al. 2011; Curriero et al. 2002; McMichael et al. 2008) and over time using longer time series data (Honda et al. 2006). Our exploratory analyses suggested that such an approach would be even more limited in power, for UHI decile groups within a single city such as London, than the approaches we used. Also we preferred not to assume constant slopes in different UHI decile groups. Hence, we favour the 'shifted spline' approach because it requires less restrictive assumptions and makes fuller use of the data than most alternatives, and it is amenable to relatively straightforward statistical inference on extent of acclimatization. Nonetheless, we recognise that acclimatization could result in other transformations in shape of the temperature-mortality function.

Applied to London, our methods yielded relatively imprecise estimates of UHI acclimatization. For heat this may in part be because of the limited number of days in London with heat-related mortality. This may also explain the contrast of our results with studies finding higher heat risks in areas more affected by UHI, which were all in cities with higher proportion of heat-affected days (Goggins et al. 2012; Goggins et al. 2013) as indicated by the MMTs found by (Gasparrini et al. (2015)). However, it was a surprise that there was not more power to discriminate between *full* and *no* acclimatization for cold, which accounts for a much larger overall burden of mortality in London. Here the limitation seems to have been due to the less steep `slope' for cold compared to heat mortality (1.03/^{o}C compared to 1.07/^{o}C) which makes cold-mortality associations in localities with different UHIas harder to discriminate.

CONCLUSIONS

We have proposed and applied analytical methods that provide quantitative estimates of the degree of acclimatization to the heat- and cold-related mortality burdens associated with the UHI effect by comparing differences over area rather than changes over time. For London, our evidence suggests relatively *full* acclimatization to the UHI effect on summer heat-related mortality, but less clear evidence on extent of acclimatization to the UHI effect on cold deaths. Evidence just for London of the ability to acclimatize to the modest summer increments in temperatures related to the UHI has limited relevance to policies to protect against the future heat effects within cities under climate change, but these methods could be applied to larger populations to inform policies.

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Table 1. UHI anomaly[a], deprivation index[b] and all cause deaths for London UHI anomaly decile groups[c]

UHI decile groups[c]	Mean UHIa[a] (^{0}C)	Mean deprivation index[b] (z-score)	Number of all cause deaths	% of 75+ years old deaths
Group 1	-0.93	-0.62	23,170	66.7
Group 2	-0.51	-0.41	44,007	67.5
Group 3	-0.26	-0.41	63,721	66.5
Group 4	-0.11	-0.28	76,293	64.3
Group 5	0.01	-0.17	83,281	63.0
Group 6	0.12	-0.33	87,214	62.1
Group 7	0.23	-0.03	99,339	61.5
Group 8	0.34	0.33	103,658	60.5
Group 9	0.47	0.78	130,458	55.4
Group 10	0.63	1.18	132,396	52.7

Abbreviations: UHI, urban heat island; UHIa(s), urban heat island anomaly (anomalies).

[a]UHI anomaly is the annual average of the daily excess temperature at each grid relative to the average temperature on the same day in London as a whole. [b]Deprivation index was reconstructed from English Index of Multiple Deprivation 2004 excluding the health and disability domains and the living environment domains. [c]UHI decile groups were defined by the deciles of all grid UHIas in London. Group1 represents the smallest UHI anomaly group and Group10 does the largest UHI anomaly group.

Table 2. Heat- and cold-related RRs[a] at UHIa[b] of +0.5 and -0.5°C and observed IRRs[c] and those expected if there were no acclimatization[d].

Exposure	UHIa[b] (°C)	RR[a] (95%CI)	IRR[c] (95%CI)	Expected IRR (95%CI) assuming *no* acclimatization[d]
Heat	- 0.5	1.203 (1.154, 1.255)	1	1
	+ 0.5	1.208 (1.176, 1.241)	1.004 (0.950, 1.061)	1.070 (1.057, 1.082)
Cold	+ 0.5	1.129 (1.106, 1.152)	1	1
	- 0.5	1.152 (1.116, 1.189)	1.020 (0.979, 1.063)	1.030 (1.026, 1.034)

Abbreviations: RR, relative risk; UHIa(s), Urban Heat Island anomaly(ies); IRR, interaction rate ratio. [a]RRs of mortality for heat and cold days with daily mean temperatures > 22.3 °C or < 6.4 °C (respectively) compared to days with daily mean temperatures ≥6.4 and ≤ 22.3 °C, with lag0–1 or lag0–13 (respectively) and adjustment for the day of the week and for influenza counts. [b]UHIa was defined as the average of excess daily mean temperature (°C) at 1km grid compared to the London overall temperature. [c]Ratios of the RR for heat in UHIa +0.5 vs. -0.5 °C, or of the RR for cold in UHIa -0.5 vs. 0.5 °C. [d]Expected IRRs are generated by modelling the association between mortality and daily mean temperature for London as a whole using a linear spline with knots at 18.6 °C (the minimum mortality temperature) and at 22.3 °C (for heat) or at 6.4 °C and 18.6 °C (for cold), with each IRR representing the risk of mortality with a 1°C increase in daily mean temperature > 22.3 °C or < 6.4 °C for heat and cold, respectively.

FIGURE LEGENDS

Figure 1. London urban heat island (UHI) anomaly decile groups. UHI anomaly was defined by the annual mean of daily excess temperature at each grid relative to the average temperature on the same day in London as a whole. Decile group 1 represents the lowest UHI anomalies (coolest) and group 10 does the highest UHI anomalies (hottest).

Figure 2. Temperature-mortality functions assuming acclimatization is neutral (γ=0.5) between *full* (γ=0) and *none* (γ=1) (left) and deviances of lateral displacement for values of γ in the range -0.5 to 1.5 ˚C (right) for summer heat (lags 0 to 1 days, June to August) [A] and winter cold (lags 0 to 13 days, September to May) [B]. Gray shading in the temperature mortality functions represents 95% CI. Deviances were calculated against that for maximum likelihood estimate (MLE). Likelihood ratio test (LRT) was applied for differences between deviances at γ =1 and γ =0.

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Figure 1.

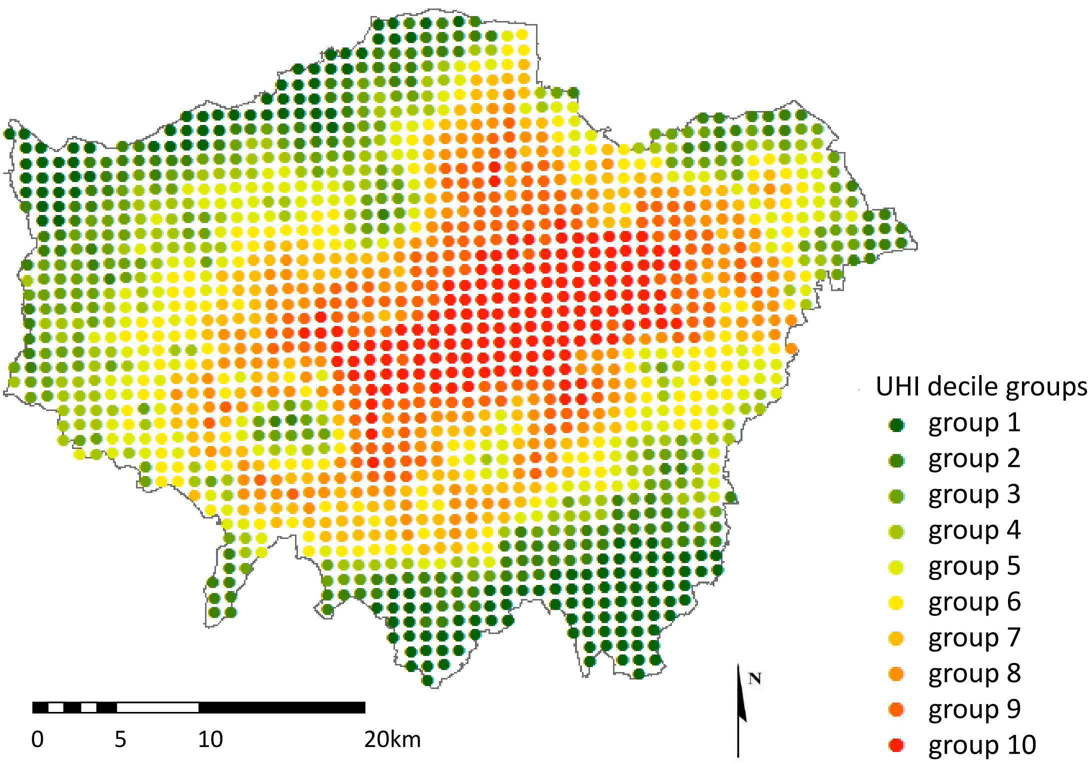
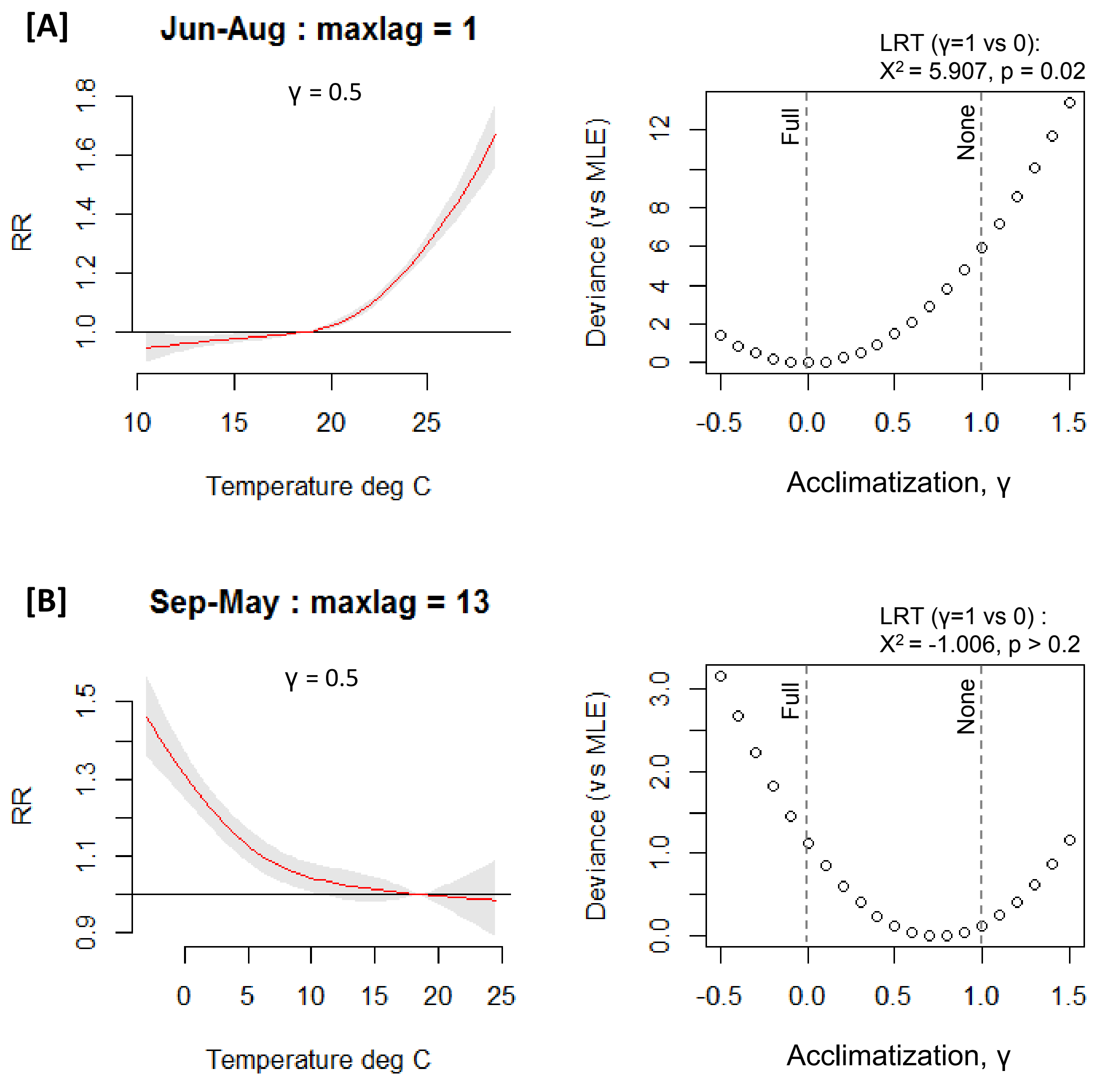


Figure 2.


[A]
Jun-Aug : maxlag = 1
γ = 0.5
RR
1.0
1.2
1.4
1.6
1.8
10
15
20
25
Temperature deg C
LRT (γ=1 vs 0):
X² = 5.907, p = 0.02
Deviance (vs MLE)
0
2
4
6
8
12
Full
None
-0.5
0.0
0.5
1.0
1.5
Acclimatization, γ
[B]
Sep-May : maxlag = 13
γ = 0.5
RR
0.9
1.1
1.3
1.5
0
5
10
15
20
25
Temperature deg C
LRT (γ=1 vs 0) :
X² = -1.006, p > 0.2
Deviance (vs MLE)
0.0
1.0
2.0
3.0
Full
None
-0.5
0.0
0.5
1.0
1.5
Acclimatization, γ